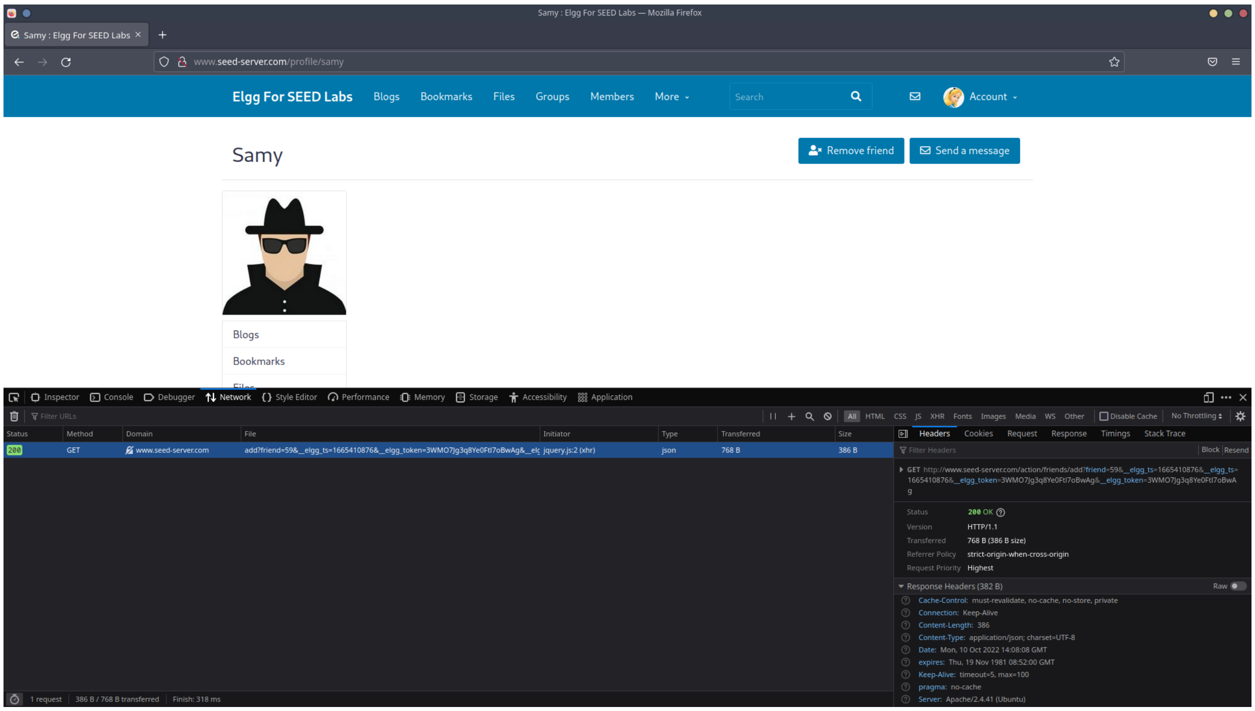
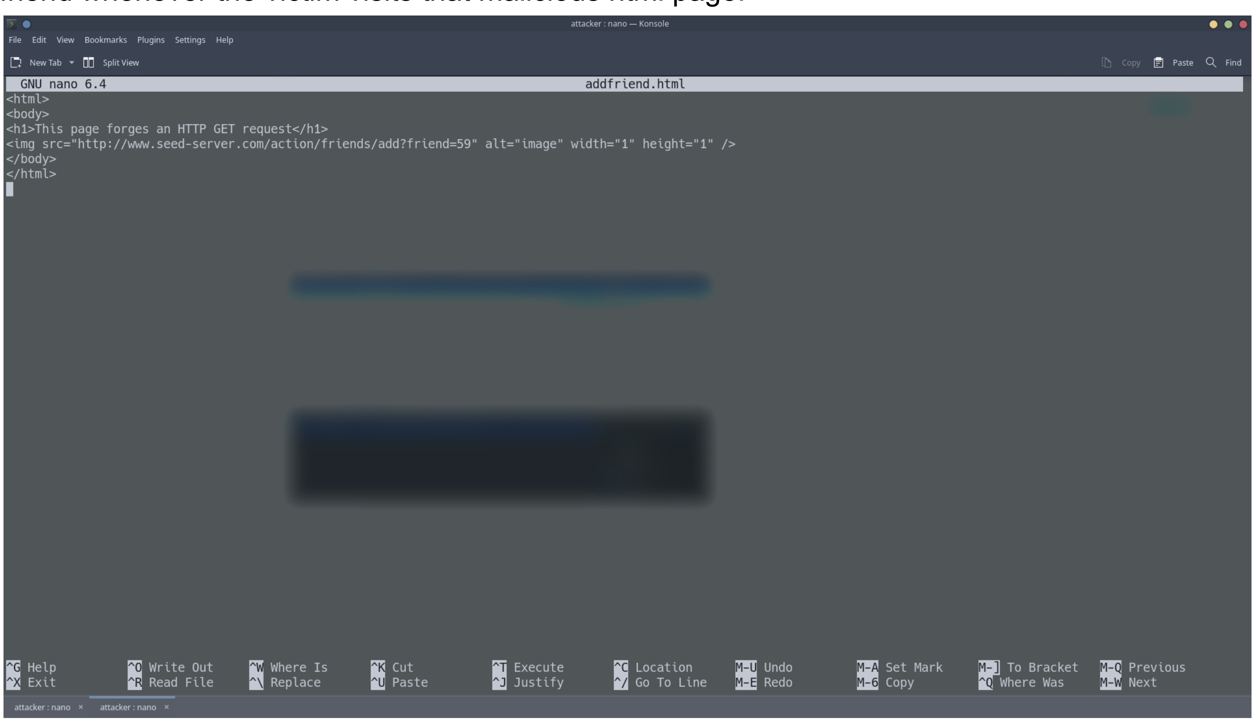
Task-1

We check the GET request which is sent to the server when Samy is added as a friend. From that request we get the URL and the guid number of Samy.

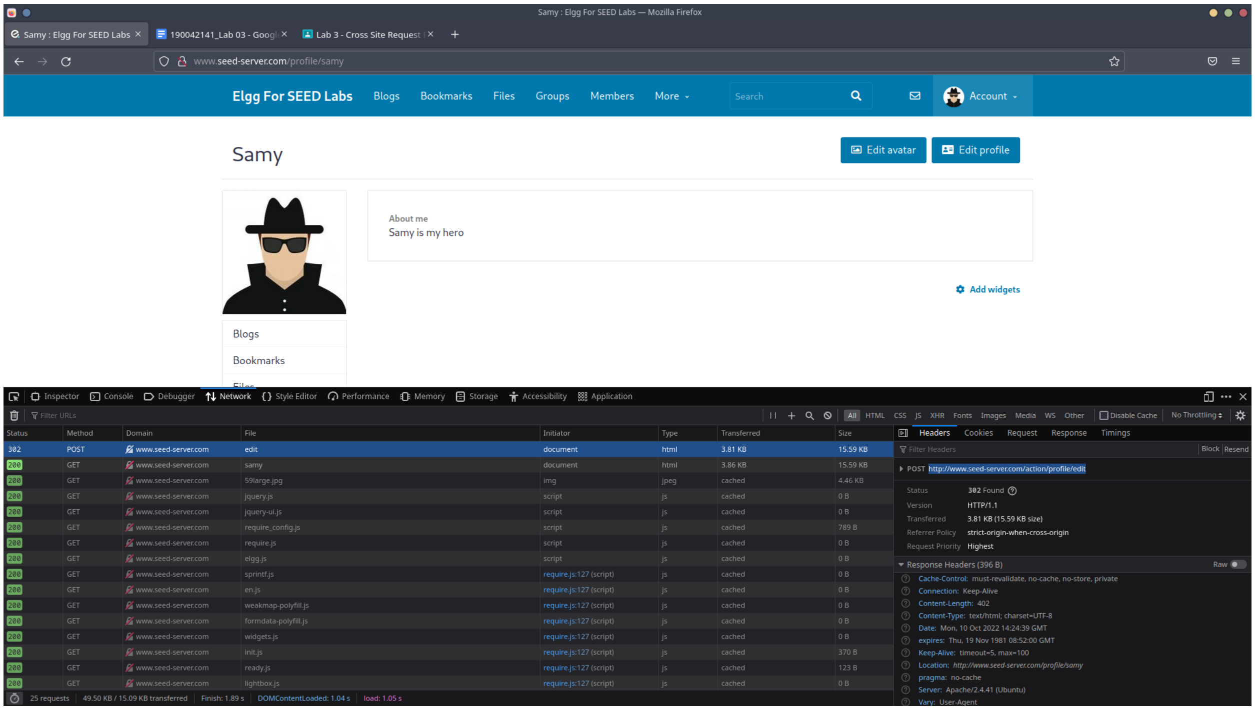


So we make a forged request using a html file where we send the request to add Samy as a friend whenever the victim visits that malicious html page.

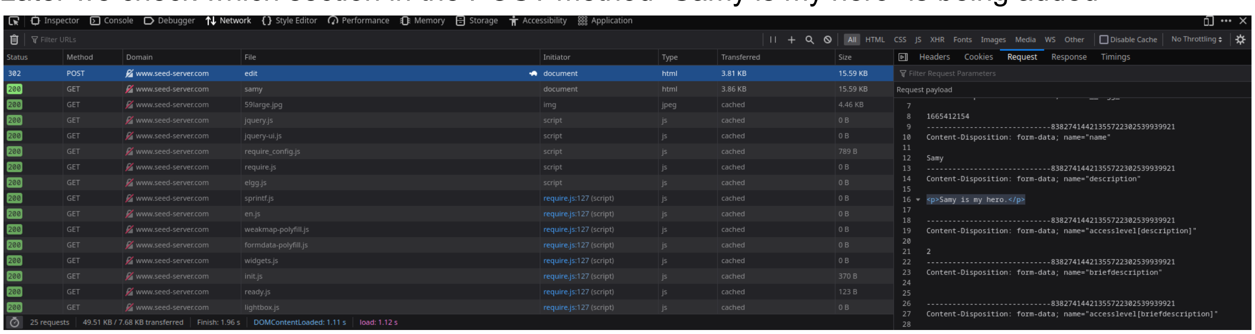


Task-2

At first we find out the URL which is required to POST any request to the profile using Samy's profile. We get the required URL for editing any profile-
`http://www.seed-server.com/action/profile/edit`

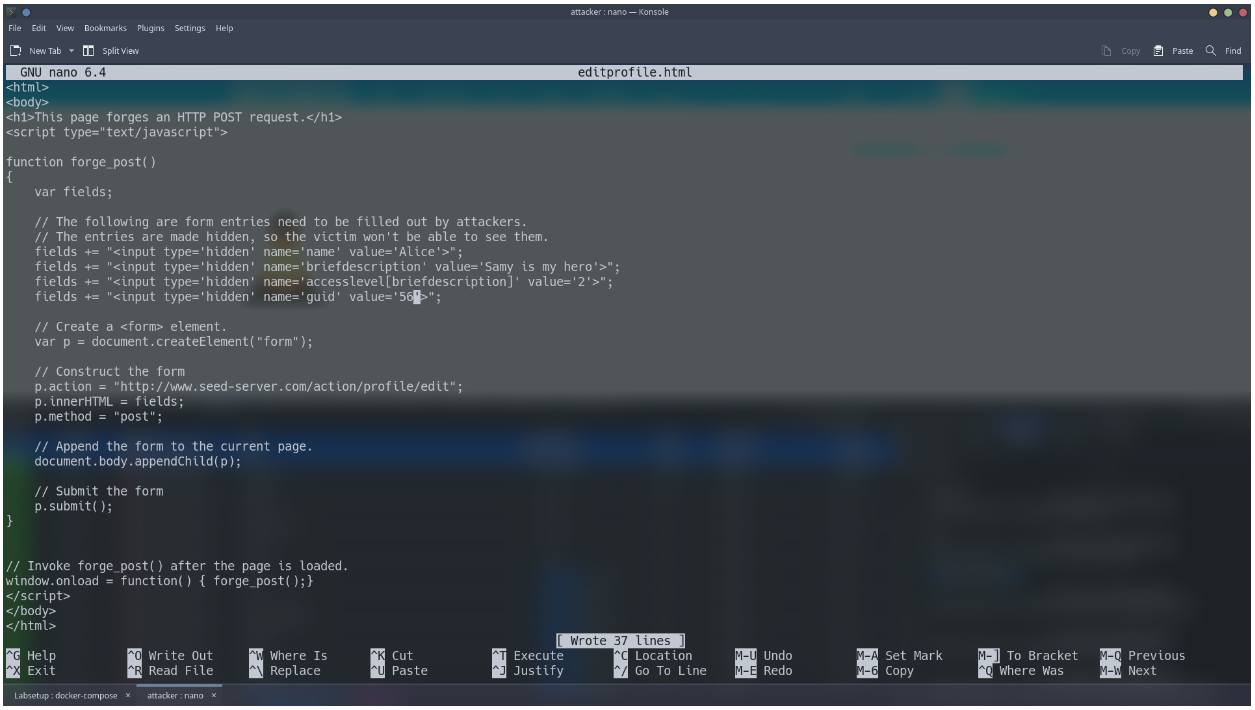


Later we check which section in the POST method "Samy is my hero" is being added

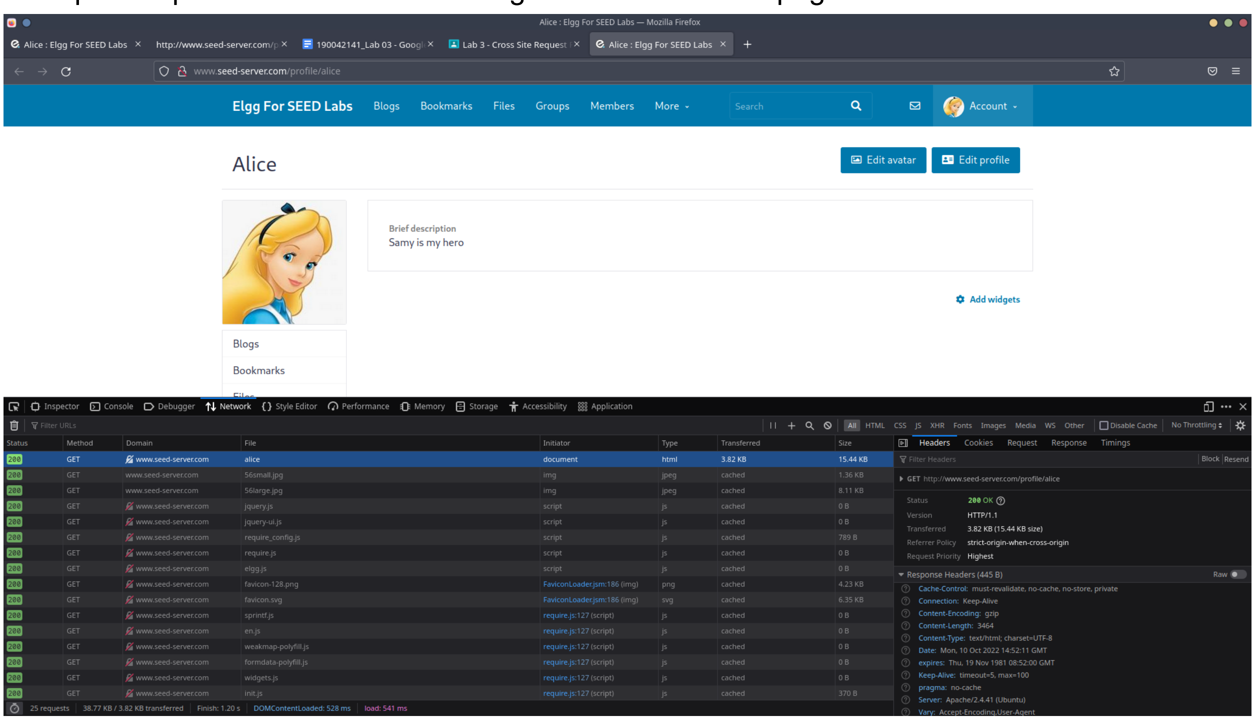


Later we find the guid number of Alice from page source

As we now know the required fields where we need to edit, we create a malicious html page in which when Alice clicks her profile will be edited by making a forged request

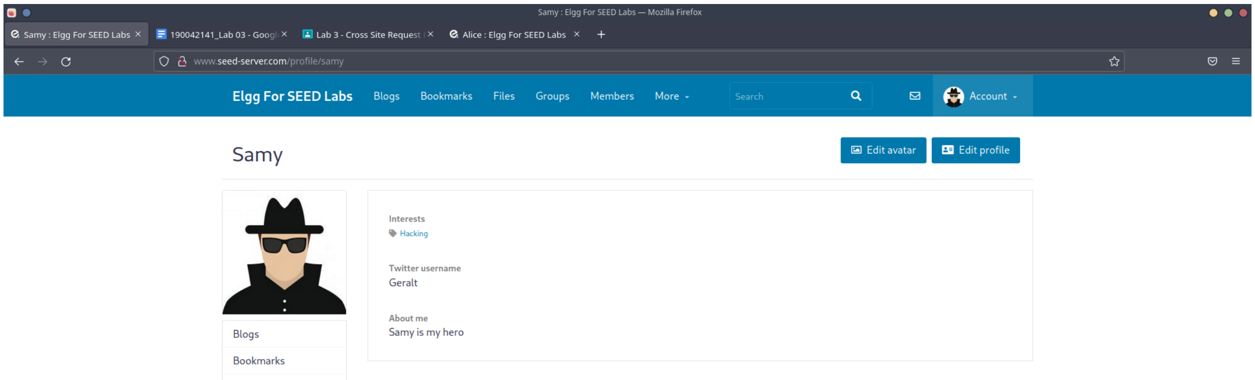


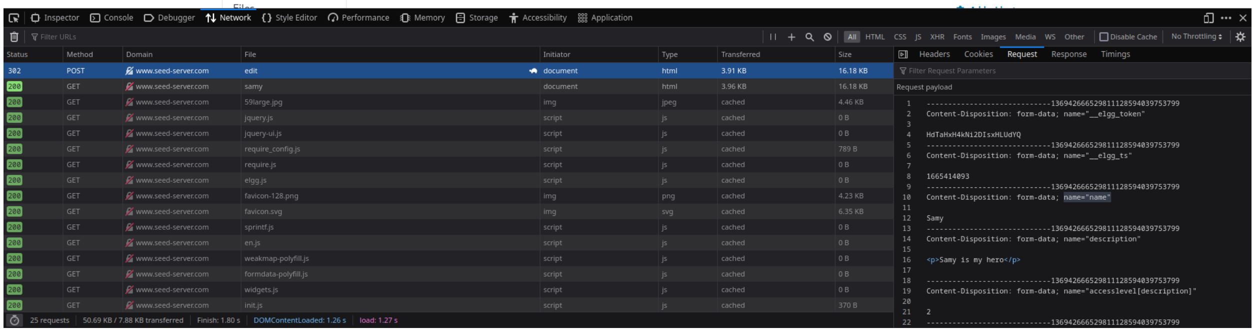
The updated profile of Alice after clicking the malicious html page

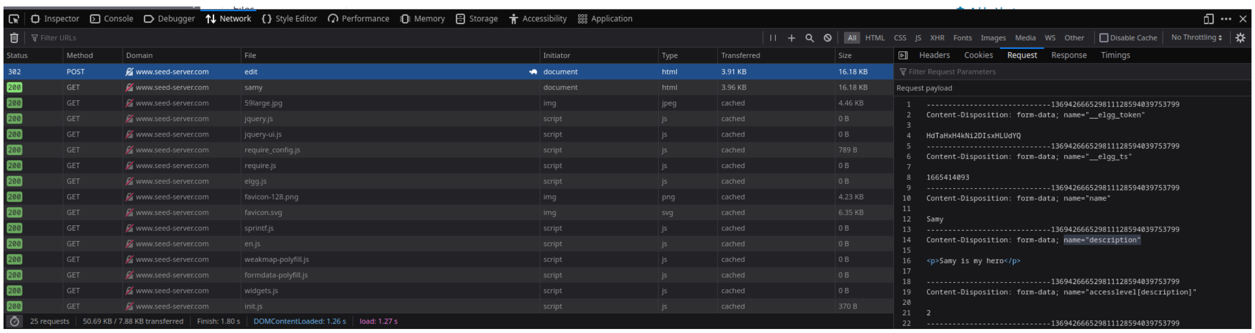


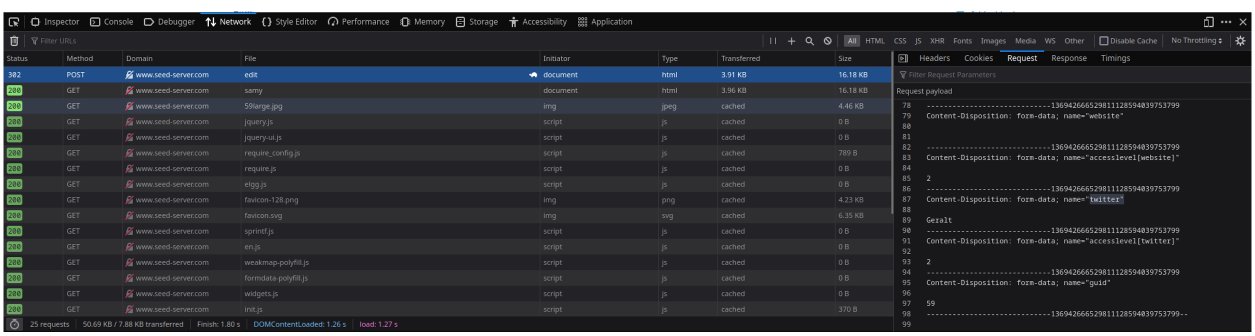
Task-3

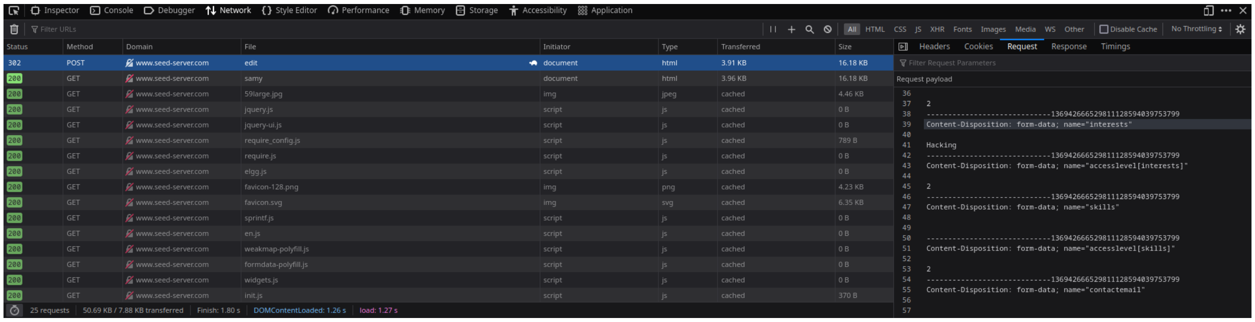
Same as the previous task we get the profile edit URL link. When we edit the profile of Samy in the fields of brief description, interests, twitter according to the requirements of the task. Later we check the fields in the html code where modifications are made.



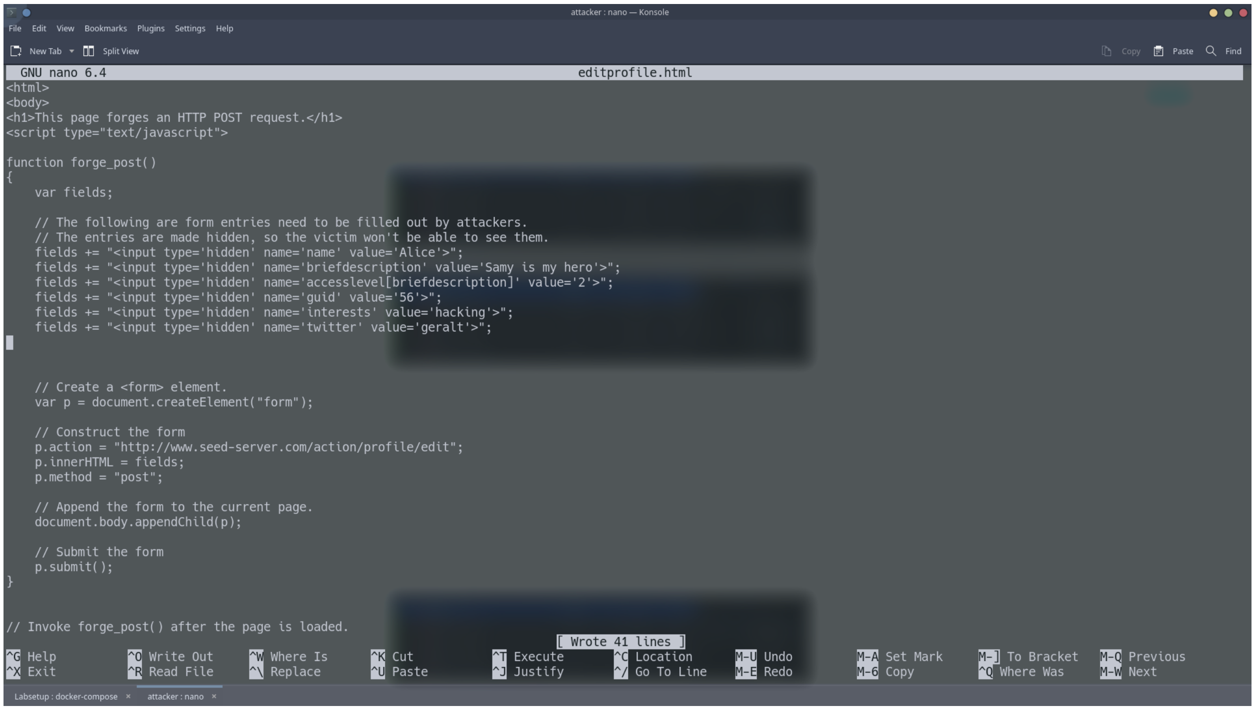


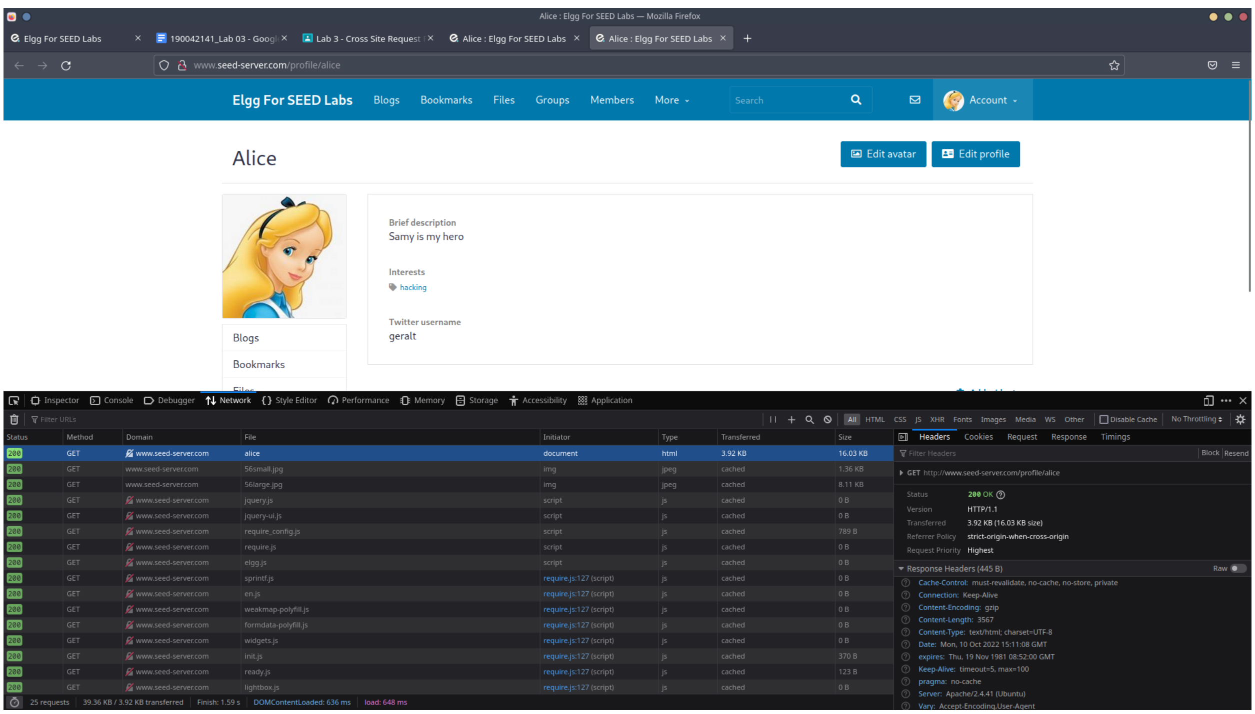






Now after getting the field and its names we modify the previous html code. We add two extra fields to change the interest and twitter field. We give the values with which we want to modify the required profile of Alice

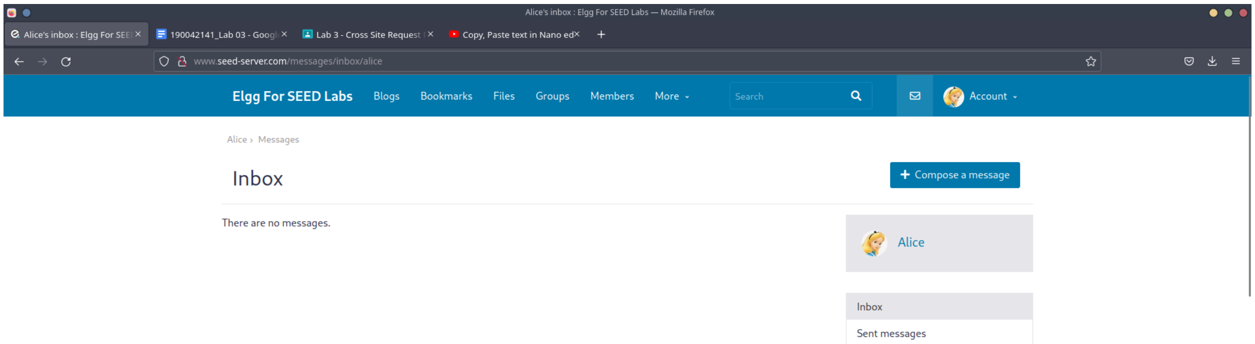


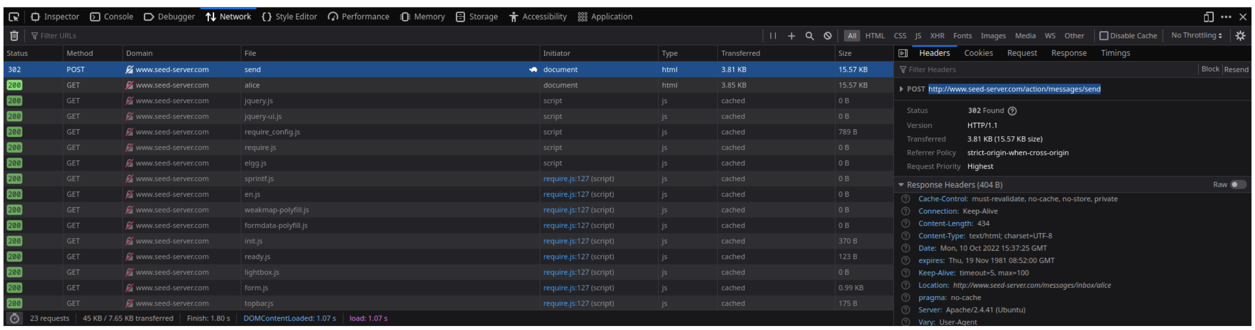


After modifying the malicious html script we send it to Alice. When Alice clicks the malicious link the html code will produce a forged request to modify the profile of Alice

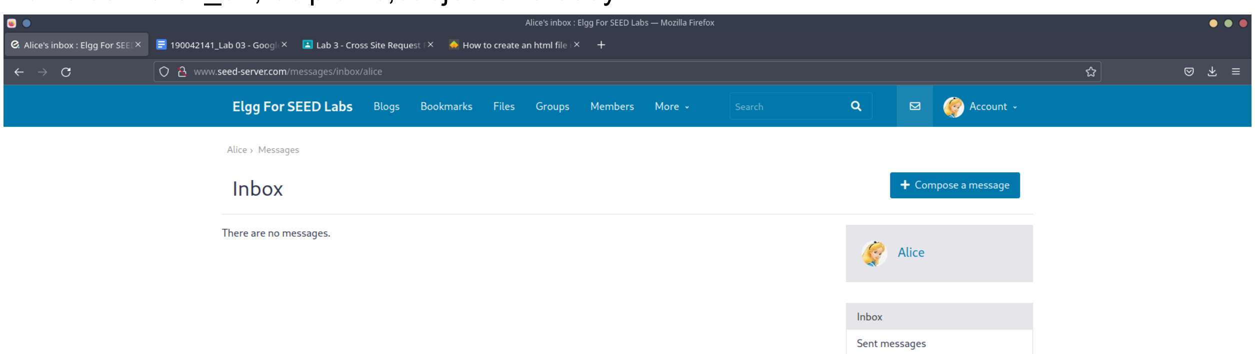
Task-4

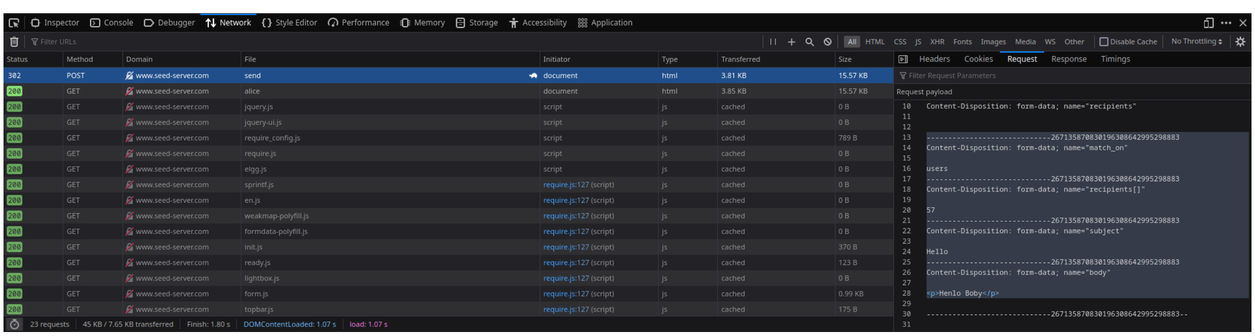
At first we send a dummy message to Boby to check the URL request sent during messaging. As a result we get the required URL-
"http://www.seed-server.com/action/messages/send"



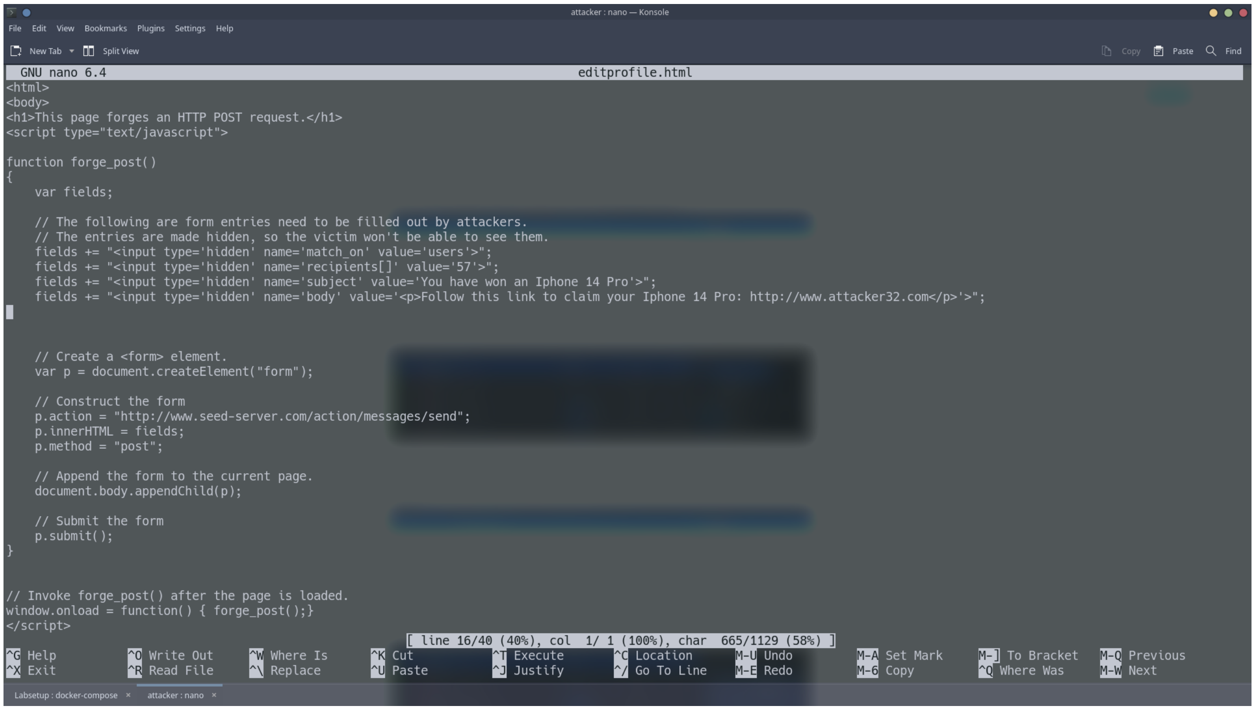


Later we check the fields which are modified during sending the request. As a result we get that the fields match_on,recipients,subject and body

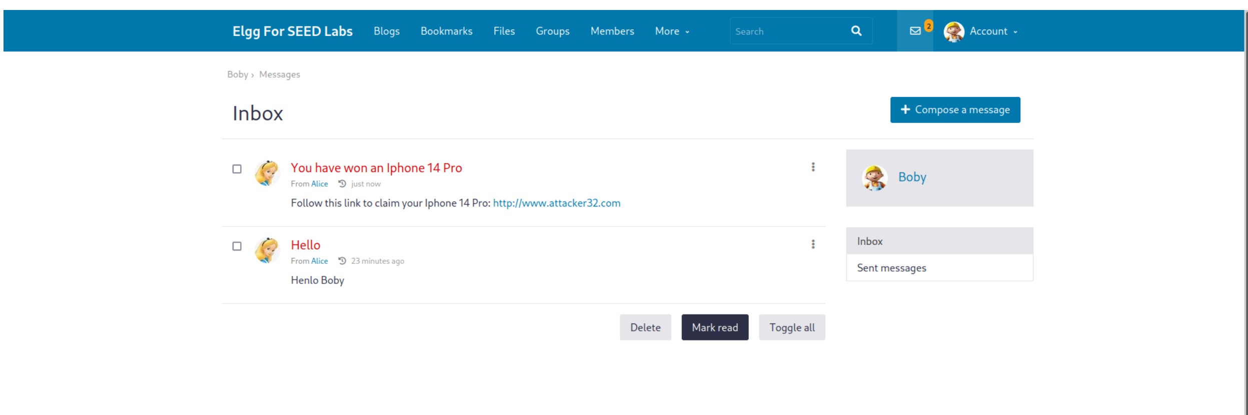




So we change the edit-profile html page with the required fields and the required values against those fields to make a forged request using this malicious html page



Here when Alice goes to that malicious website a message is sent to Boby and the message contains the link **www.attacker32.com**



A machine learning algorithm based on decision trees is called Random Forest Trees (RFT). Machine learning algorithms that do ensemble classification include Random Trees (RT). The term "ensemble" denotes a technique that averages the forecasts of various different base models to provide predictions.
The core idea behind ensemble methods based on randomization is to "incorporate random perturbations into the learning procedure to build multiple alternative models from a single learning set L and then to aggregate the predictions of those models to make the ensemble prediction" (Louppe, 2014). In other words, "growing an ensemble of trees and letting them vote for the most popular class has resulted in significant gains in classification accuracy. These ensembles are frequently grown by creating random vectors that control how each tree in the ensemble grows (Breiman, 2001).

When building a random tree, there are three basic options available. These three considerations are: (1) how to separate leaves; (2) what kind of predictor to utilize in each leaf; and (3) how to introduce unpredictability into trees (Denil et al., 2014). Using a bootstrapped or sub-sampled data set to generate each tree is a typical method for adding unpredictability to a tree. As a result, there are variances among the trees in the forest since each tree in the forest was trained using slightly different data (Denil et al., 2014). The optimal split at a particular node can alternatively be chosen randomly; tests have shown, however, that where noise is relevant, bagging typically produces better results (Louppe, 2014).

"Special attention must be taken so that the resulting model is neither too simple nor too complex," according to the author, when optimizing a Random Trees model. The model is in fact stated to have underfitted the data in the first scenario, i.e., it was not adaptable enough to capture the structure between X and Y. The model is said to be overfit the data in the latter scenario because it is too flexible and captures isolated structures (i.e., noise) that are unique to the learning set (Louppe, 2014).

In order to prevent overfitting, stropping rules must be established to stop a tree from developing before it has too many levels: User-defined hyper-parameters are used to establish stopping conditions (Louppe, 2014). The most popular of these parameters are:
The bare minimum of samples that a terminal node needs to divide
the bare minimum of samples in a leaf node after splitting the terminal node
The maximum depth of a tree, or the number of levels it can reach,
once the Gini Impurity index, which measures the Trees accuracy, falls below a predetermined threshold
To identify the best trade-off, these parameters must be fine-tuned; they must be neither too stringent nor too loose for the tree to be neither too shallow nor too deep (Louppe, 2014).
Breiman (2002) lists the following as some of the essential characteristics of random trees:
It is a very good classifier, with accuracy on par with support vector machines.
As the forest grows, it produces an internal, unbiased estimate of the generalization error.
When up to 80% of the data are missing, it nevertheless retains accuracy thanks to an efficient estimation algorithm.
It has a technique for balancing inaccuracy in data sets with an imbalanced class population.

The generated forests can be saved for use on other data in the future.
It provides an estimate of the variables that are crucial for classification.
Information regarding the relationship between the variables and the categorization is shown in the output that is produced.
It calculates distances between examples that can be used for grouping, finding outliers, or scaling to provide intriguing data visualizations.
Contrary to the Support Vector Machine (SVM), the random trees classifier can typically handle a mix of categorical and numerical variables. As for data scaling, Random Trees are less susceptible to it than SVM, which frequently requires data to be normalized before training or classification. SVM is said to perform better, nonetheless, when the training set is little or uneven. Comparable in computational complexity to SVM, the Random Trees classifier performs better and more quickly with big training sets.